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UNCERTAINTY ESTIMATION OF IMAGE-BASED MEASUREMENTS AFFECTED BY MOTION BLUR

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ABSTRACT

The paper describes a new automated approach to the uncertainty estimation of image-based measurements affected by motion blur. Due to the upward trend to the integration of quality assurance in production processes, image-based measurements are executed in motion or on motion-blurred units under test. In that context new requirements are made on the measurement process and the estimation of measurement uncertainty. The main purpose of this paper is to present the interrelationship between the motion speed during the measurement and the estimation value of the measurement uncertainty.

Index Terms - motion-blurred images, image-based measurements, quality assurance measurement uncertainty, deconvolution algorithm

1. INTRODUCTION

There is the mainstream trend of using image sensors in quality assurance due to their large scope of application, their short measurement time, their contactless operation mode, their large operating distance, their concomitant large measuring range and their flexibility in the measurement of different workpieces. Furthermore, measurement processes are increasingly integrated in the production area associated with high requirements on the robustness of the measurement instruments. Quite often measurements should realised in motion or on motion-blurred units under test e. g. measurements integrated in assembly line production. The aim is to adopt the measurement on the production frequency or the speed of the assembly line. Despite of these conditions the measurements should be realised with an adequate measurement uncertainty [1].
The subject matter of this paper is to demonstrate a procedure suitable for estimating the measurement uncertainty of image-based measurements affected on motion blur [2] and to show the relation between the motion speed and the associated estimated measurement uncertainty.

2. INTEGRATED UNCERTANTY ESTIMATION PROCEDURE

Integrated in the measurement process, especially the detection of edges on inspection features within an image, the current uncertainty is estimated based on image quality indicators (IQIs). Via Monte-Carlo method [3] standard uncertainties are propagated to the expanded measurement uncertainty of the measurand. The uncertainty estimation is realised using an inference function where the IQIs serve as variables. The inference function is built on the knowledge acquired within pre-examination. By using current IQIs the inference function is refreshed in each measurement automatically [4, 5]. The complete measurement result composed of the best estimate and the expanded measurement uncertainty is indicated according to [1].

3. EXEMPLIFICATION OF THE PROCEDURE IN IMAGE-BASED MEASUREMENTS AFFECTED BY MOTION BLUR

3.1. Point Measurements

Testing the uncertainty procedure in motion-blurred images, as expected, it was determined that the uncertainty of image measurements with higher speed is also significant higher than in images with lower speed (Fig. 1 - 4). The point measurements were realised in subpixel-precision on a chrome-glass standard. For examining the measurement uncertainty only the subpixel-precise edge position (SPEP) is used.

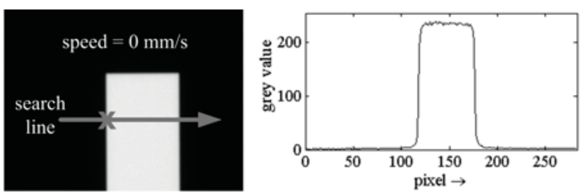

Fig. 1: Point-Measurement on an edge without motion blur, SPEP = 117.9568 ± 0.0156 pixel.

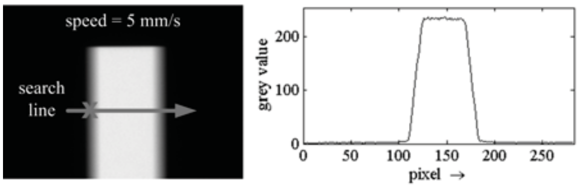

Fig. 2: Point-Measurement on an edge with motion blur, speed = 5 mm/s, SPEP = 117.8439 ± 0.0543 pixel.

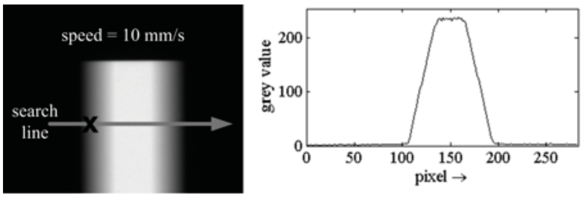

Fig. 3: Point-Measurement on an edge with motion blur, speed = 10 mm/s, SPEP = 120.6562 ± 0.4745 pixel.

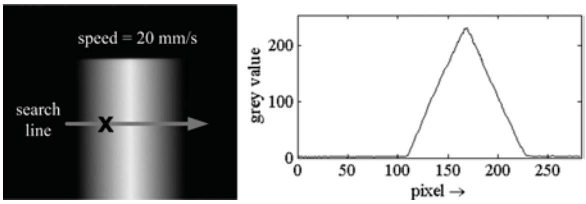

Fig. 4: Point-Measurement on an edge with motion blur, speed = 20 mm/s, SPEP = 135.7792 ± 4.2063 pixel.

Comparing the uncertainties of the subpixel-precise edge positions (SPEPs) in dependence on the speed the following chart results (Fig. 5).

The high uncertainty in figure 4 with speed = 20 mm/s results due to the fact that the feature under test is to small in their width. Consequently the edges on the left and the right site of the class structure are blurred and merged. The white area is nearly omitted due to the expansion of the both edges.

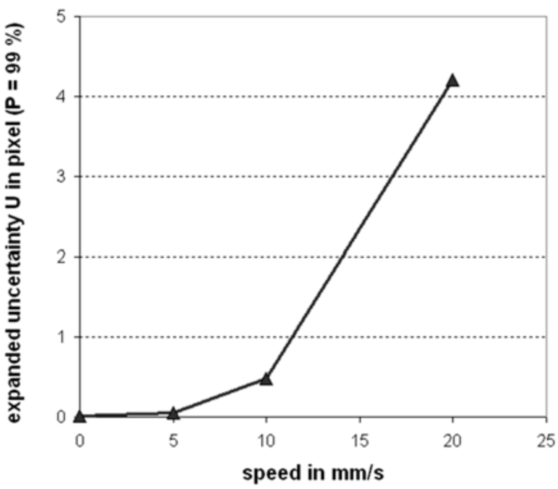

Fig. 5: Measurement uncertainty in dependence on the speed in motion-blurred image measurements.

3.2. Distance Measurements

Typical measuring tasks in quality assurance are distance measurements. Another aim of this paper is to investigate the measurement uncertainty of motion-blurred distance measurements.
The measuring task in particular is visualized by figure 6 on a chrome-glass standard.

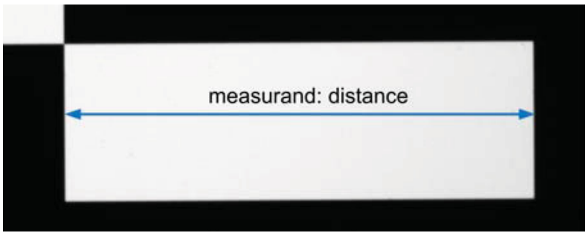

Fig. 6: Measuring task: Distance measurement on a chrome-glass standard.

The measuring procedure consists of two straight-line measurements (Fig. 7). Therefore an rectangular area of interest (AOI) with 50 search lines is used. The search lines are orthogonally aligned to the edge. All detected edge points are used to fit a straight-line. For the distance calculation the both parameter vectors of the left straight-line (start-point vector and directional vector) and the start-point vector of the right straight-line are used. Consequently in a mathematical point of view, it is a question of a straight-line-point distance calculation.

Fig. 7: Measuring procedure: Straight-line-point distance calculation. Example: Speed = 5 mm/s.

In the following the distance and its uncertainty are measured in dependence on the speed. For uncertainty calculation the standard uncertainties of the detected edge points are propagated using the Monte Carlo method with 10 000 iterations [3].

The feature under test for the distance measurement has a higher width in comparison to the point measurements. In this way the blurring of both edges into each other should be avoided.

Figures 8 - 12 show the results of the distance measurements for different motion speed.

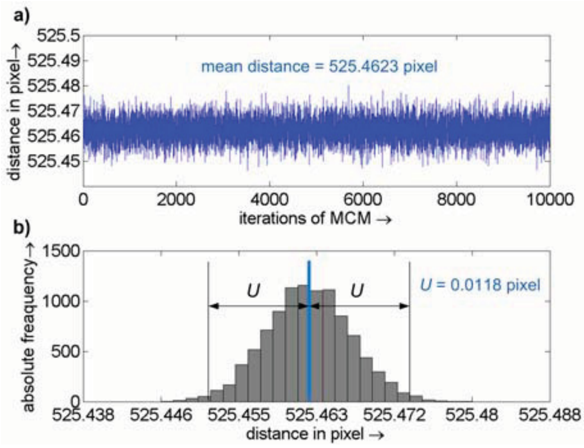

Fig. 8: Distance Measurement: a) distance values in Monte Carlo simulation; b) histogram with expanded uncertainty U for a coverage interval P = 99 %, speed = 0 mm/s.

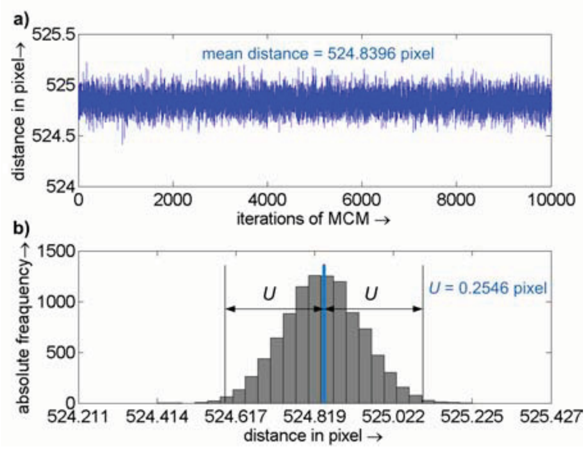

Fig. 9: Distance Measurement: a) distance values in Monte Carlo simulation; b) histogram with expanded uncertainty U for a coverage interval P = 99 %, speed = 5 mm/s.

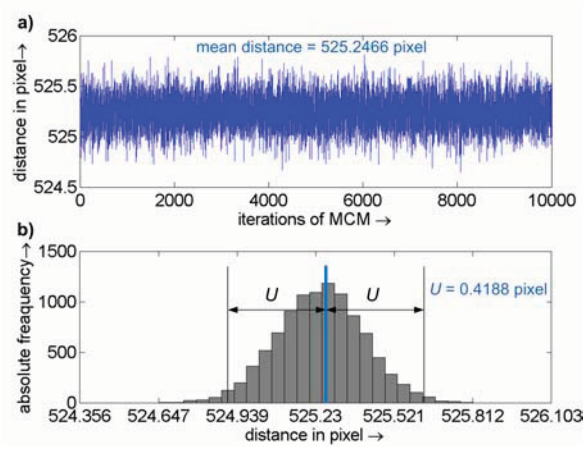

Fig. 10: Distance Measurement: a) distance values in Monte Carlo simulation; b) histogram with expanded uncertainty U for a coverage interval P = 99 %, speed = 10 mm/s.

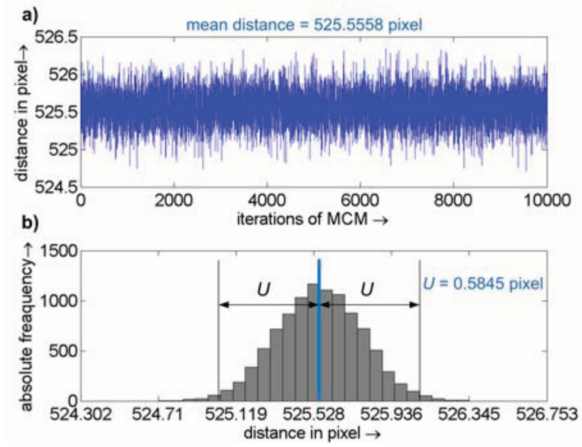

Fig. 11: Distance Measurement: a) distance values in Monte Carlo simulation; b) histogram with expanded uncertainty U for a coverage interval P = 99 %, speed = 15 mm/s.

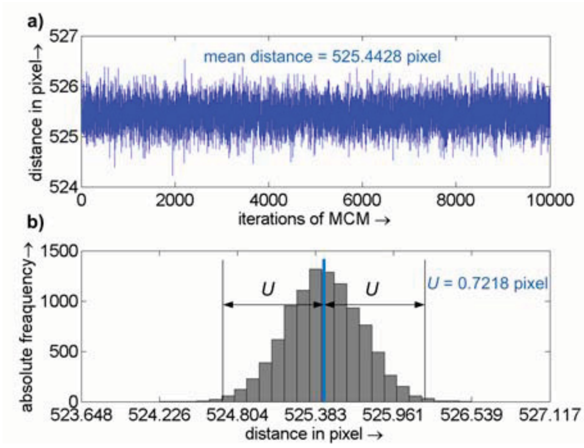

Fig. 12: Distance Measurement: a) distance values in Monte Carlo simulation; b) histogram with expanded uncertainty U for a coverage interval P = 99 %, speed = 20 mm/s.

Comparing the uncertainties of the subpixel-precise distance measurements in dependence on the speed the following chart results (Fig. 13).

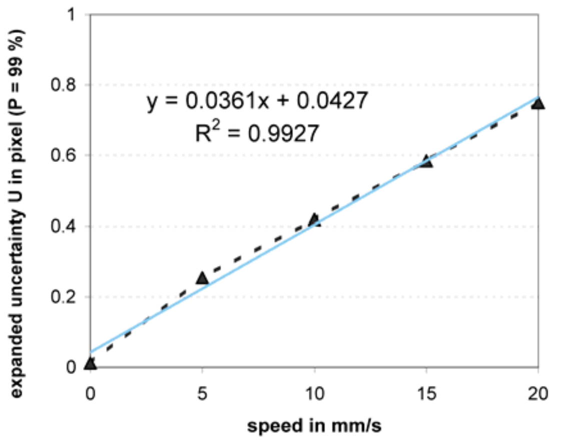

Fig. 13: Measurement uncertainty in dependence on the speed in motion-blurred image measurements.

On the one hand it is ascertainable that the uncertainty values of the distance measurements are considerably lower than the uncertainties of the point measurements. The reason is, that the calculation of distance uncertainties is based on the propagation of respectively 50 point measurements with associated uncertainties for each of the straight lines. The decreased uncertainty of the distance measurement is effected by the concentration of information and the utilisation of fitting and propagation algorithms.

On the other hand contrary to the point measurement uncertainties, the distance measurement uncertainties run with a nearly linear trend. The approximated linear equation has a stability index of $R^2 = 0.9927$.

Based on this the linear function the uncertainty forecasting in production processes is realizable - especially in the inspection planning and for the optimization of measuring times and costs in dependence on the tolerances.

Another important fact in addition to the analysis of uncertainties is the deviation of the measurement value itself (Fig. 14). Thus, it appears that no linear trend is available.

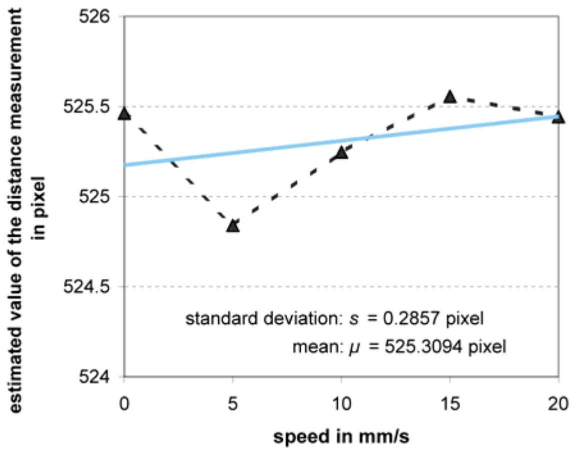

Fig. 14: Estimated values of the distance measurement in dependence on the speed in motion-blurred images.

4. AOI-BASED ITERATIVE RESTORATION ALGORITHM

The proposed method is an AOI-based iterative restoration algorithm for motion deblurring. The restoration i.e. deconvolution is iteratively performed by determination of the blurred edge width (BEW), which is used to generate the point spread function (PSF). The obtained PSF is further used by deconvolution. Presently the Richardson-Lucy algorithm is chosen and brings the ring-effect in the restored image. A post-processing is performed to wipe off the ring-effect and deliver the ‘clean’ image (AOI-data) to the next iteration. The iterative procedure ends until the BEW value reaches a predefined value (small enough) or a maximum number of iteration is achieved [2].

The algorithm was developed within the subproject: *Deconvolution algorithms for compensation of motion blur*. Figure 15 shows the image after deconvolution for a speed of 15 mm/s.

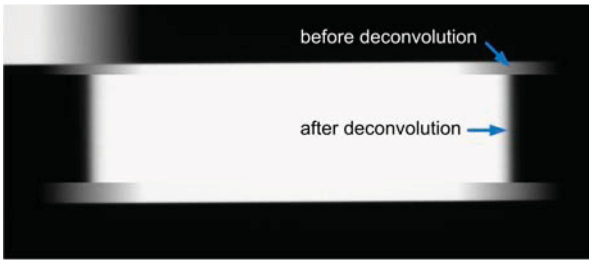

Fig. 15: Image of the feature under test after deconvolution; example: speed = 15 mm/s.

5. MEASUREMENTS IN RESTORED IMAGES

Using the new developed approach to the AOI-based iterative restoration, it is possible to restore the motion-blurred images. In the following the figures 16 - 19 show the results of the distance measurements in the restored images for different motion speed.

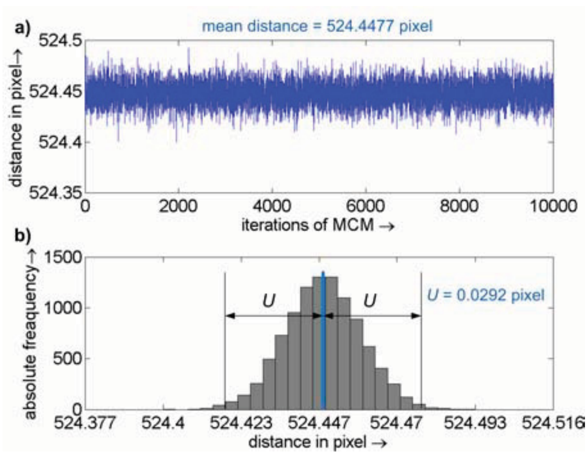

Fig. 16: Distance Measurement after deconvolution: a) distance values in Monte Carlo simulation; b) histogram with expanded uncertainty U for a coverage interval P = 99 %, speed = 5 mm/s.

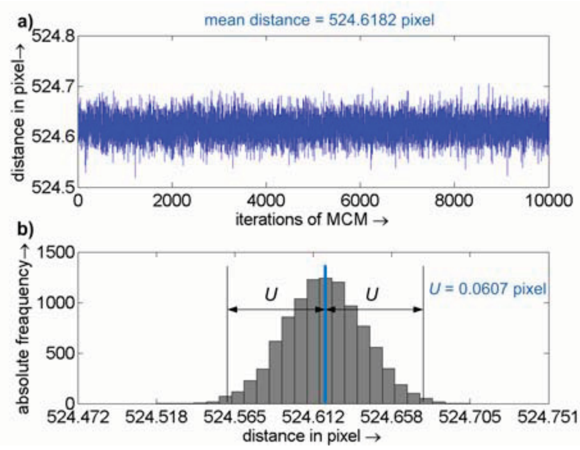

Fig. 17: Distance Measurement after deconvolution: a) distance values in Monte Carlo simulation; b) histogram with expanded uncertainty U for a coverage interval P = 99 %, speed = 10 mm/s.

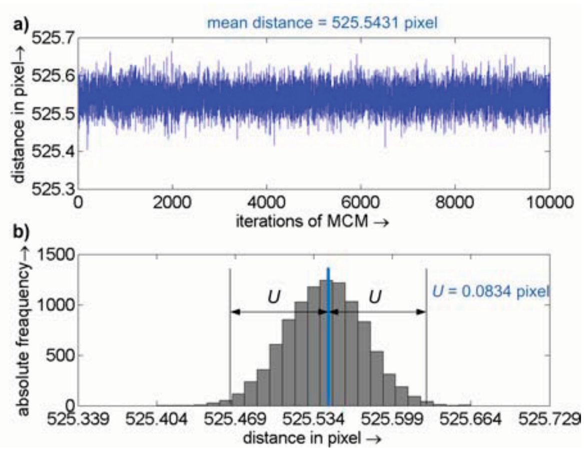

Fig. 18: Distance Measurement after deconvolution: a) distance values in Monte Carlo simulation; b) histogram with expanded uncertainty U for a coverage interval P = 99 %, speed = 15 mm/s.

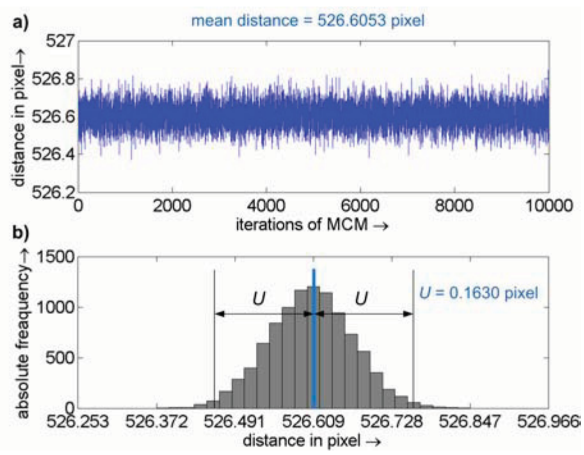

Fig. 19: Distance Measurement after deconvolution: a) distance values in Monte Carlo simulation; b) histogram with expanded uncertainty U for a coverage interval P = 99 %, speed = 20 mm/s.

Comparing the uncertainties of the subpixel-precise distance measurements after deconvolution in dependence on the speed, the chart in figure 20 results. The mean uncertainty could be reduced from 0.4039 to 0.0696 pixel. That is a decrease in uncertainty of 82.7 %. With increasing speed the uncertainty of measurements in restored images still tends upwards.

Analysing the deviation of the measurement values itself figure 21 shows no systematic movement after deconvolution (blue line) comparing with the distance values of the non-restored measurements (back line).

In total observation (Fig. 22) it was distinguished, that the deconvolution yields to an advancement of the edge detection by reducing the uncertainties. But it is not excludable, that systematic effects involve an offset in the edge position. The analysis of such systematic effects will be the topic of the further research.

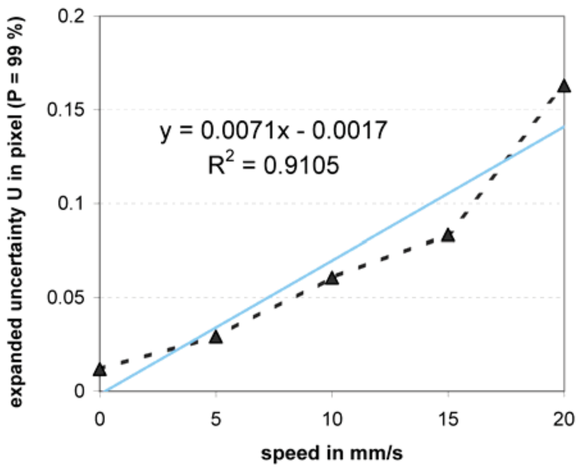

Fig. 20: Measurement uncertainty in dependence on the speed in restored image measurements.

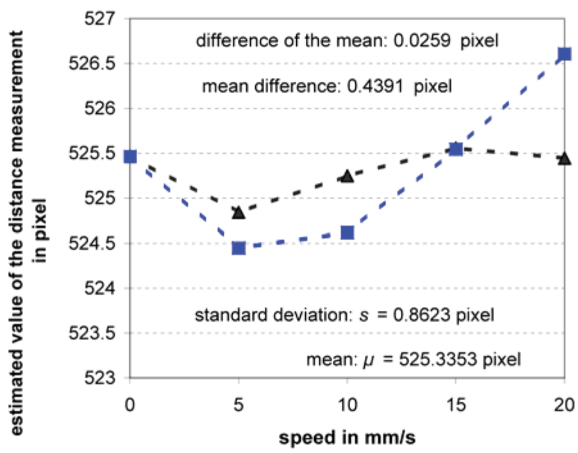

Fig. 21: Estimated values of the distance measurement in dependence on the speed in motion-blurred images (black line) and after deconvolution (blue line).

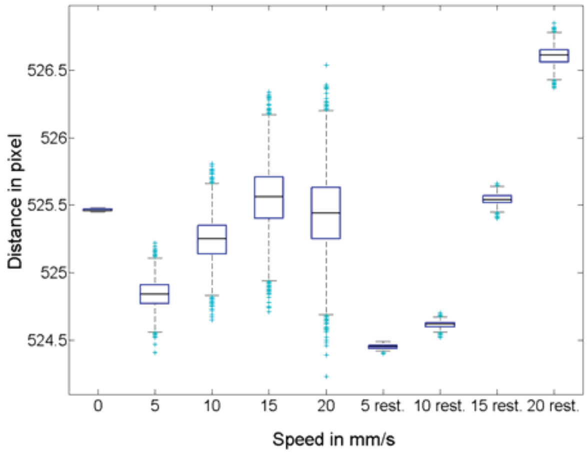

Fig. 22: Box-plot of all distance vectors (obtained using the Monte Carlo method).

6. CONCLUSION

The proposed method lays the foundations for the automated uncertainty estimation of motion-blurred image measurements. The automated estimated measurement uncertainty by this means enables the user the evaluation of the reliability of the indicated measurand.

The paper demonstrates, that the novel method gives estimates of measurement uncertainty which are practicable and widely-agreed with experimental effectuated uncertainty declarations.

Furthermore in testing the newly investigated AOI-based iterative restoration algorithm algorithms [2], the estimated uncertainty can serve as a proof of quality.

Otherwise is could pointed out that the AOI-based iterative restoration algorithm causes systematic offsets in the edge position especially for higher speeds. The analysis of such effects will be the topic of further research.

7. REFERENCES

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8. ACKNOWLEDGEMENTS

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